Milestone Report

Andy Tse

Overview

- For this report, we are going to perform an analysis on using the data that is provided by Swiftkey.
- It consists of three different files from different media outlets: news, blogs, and Twitter.
- The goal is to utilize the exploratory data analysis to determine the next word that is predicted.
- It comes in four different languages: English, Finnish, Russian, and German. In this project, the English version is going to be used in the analysis.

Getting Working Directory

```
getwd()
setwd("./Data Science Capstone")
```

Loading All the Libraries

In this component, we are going to load all the necessary packages that are going to be used in the study.

```
library(knitr)
library(tm)
library(NLP)
library(plyr)
library(SnowballC)
library(RWeka)
library(wordcloud)
library(slam)
library(stringi)
library(ggplot2)
library(dplyr)
library(R.utils)
library(openNLP)
library(textmining)
```

Loading Raw Datasets and Reading the Data

For this part, we are going to read the datasets from all media outlets. This is based off the text files that is provided from Swiftkey.

```
conn <- file("en_US.blogs.txt", open = "rb")
blogs <- readLines(conn, encoding = "UTF-8")
close(conn)

# Read news data in binary mode
conn <- file("en_US.news.txt", open = "rb")
news <- readLines(conn, encoding = "UTF-8")
close(conn)

# Read twitter data in binary mode
conn <- file("en_US.twitter.txt", open = "rb")
twits <- readLines(conn, encoding = "UTF-8")
close(conn)

rm(conn)</pre>
```

Analyzing Datasets

For this part, we are going to use the code in order to retrieve the sample data for the amount of words, lines, and other statistical component to get the information. We are gathering the data from all media outlets.

Below is the summary of all the lines for all media outlets on the data that with total lines, characters, empty lines, and words used in the files. In this information set, blogs contain 899,288 lines, the news has 1,010,242 lines, and Twitter contains 2,360,148 lines. It has been estimated that the blogs have the most for the total words, while Twitter has the most lines.

```
File Lines LinesNEmpty
                                 Chars CharsNWhite TotalWords WPL.Min.
WPL.1st.Ou. WPL.Median WPL.Mean
1 blogs 899288
                      899288 206824382
                                                                     0
                                         170389539
                                                     37570839
               41.75
9
         28
2
     news 1010242
                     1010242 203223154
                                         169860866
                                                     34494539
                                                                     1
19
                34.41
           32
3 twitter 2360148
                    2360148 162096031
                                         134082634
                                                     30451128
                                                                     1
               12.75
         12
 WPL.3rd.Qu. WPL.Max.
1
          60
                 6726
2
          46
                 1796
3
                   47
          18
```

Sample Data

We will now take a sample size of 20000 and create a random generated seed in this dataset. It will be run on a random 5% sample.

```
samplesize <- 20000
set.seed(12345)
twitSample <- twits[rbinom(length(twits)*0.05,length(twits),0.5)]
twitSample <- iconv(twitSample,'UTF-8', 'ASCII', "byte")
newsSample <- news[rbinom(length(news)*0.05,length(news),0.5)]
newsSample <- iconv(newsSample,'UTF-8', 'ASCII', "byte")
blogsSample <- blogs[rbinom(length(blogs)*0.05,length(news),0.5)]
blogsSample <- iconv(blogsSample,'UTF-8', 'ASCII', "byte")

text.Sample <- paste(twitSample,newsSample,blogsSample)

text.Sample <- Corpus(VectorSource(text.Sample))</pre>
```

Cleaning the Data

For this section, we are going clean and tidy up the data that is not useful for the analytical study. We are going to remove the unnecessary characteristics and non-English words as well.

```
# Lover Case Letter Conversion
text.Sample<- tm_map(text.Sample, tolower)

# Punctuation Removal in Text
text.Sample<- tm_map(text.Sample, removePunctuation)

# Numbers Removal in Text
text.Sample<- tm_map(text.Sample, removeNumbers)

## White Space Removal</pre>
```

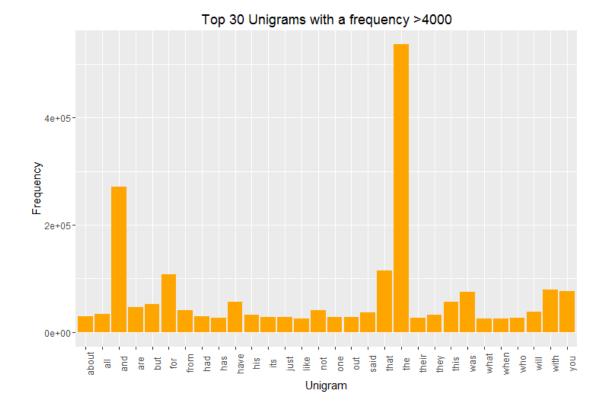
```
text.Sample <- tm_map(text.Sample, stripWhitespace)
## Plaintext Document Removal
text.Sample <- tm_map(text.Sample, PlainTextDocument)</pre>
```

Histograms

In this section below, we are going to create the histogram charts that predicts all the words in different categories. We are creating charts for the Unigram, Bigram, and Trigram analyses for frequently used words. Based on the information off the charts, we are only going to focus on the top 30 words that are used in the analysis based on what people have said in the media.

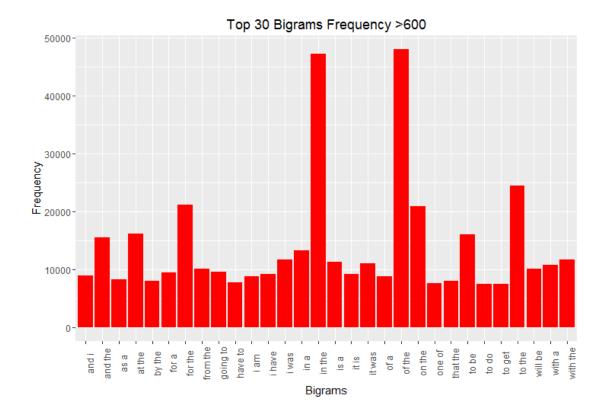
Unigrams

```
UnigramTokenizer <- function(x) NGramTokenizer(x, Weka control(min = 1,</pre>
max = 1))
text.Sample.Unigram <- TermDocumentMatrix(text.Sample, control =</pre>
list(tokenize = UnigramTokenizer))
FreqTerms <- findFreqTerms(text.Sample.Unigram, lowfreq = 4000)</pre>
text.Sample.Frequency.Vector.Uni <-
sort(rowSums(as.matrix(text.Sample.Unigram[FreqTerms,])),decreasing=TRU
text.Sample.Frequency.Dataframe.Uni <- data.frame(word =
names(text.Sample.Frequency.Vector.Uni),freq=text.Sample.Frequency.Vect
or.Uni)
ggplot(data=text.Sample.Frequency.Dataframe.Uni[1:30,],aes(x=word,y=fre
q)) +
  geom bar(stat="identity", fill="orange") +
theme(axis.text.x=element_text(angle=90)) +
  labs(title="Top 30 Unigrams with a frequency >4000") +
  labs(x="Unigram") + labs(y="Frequency")
```



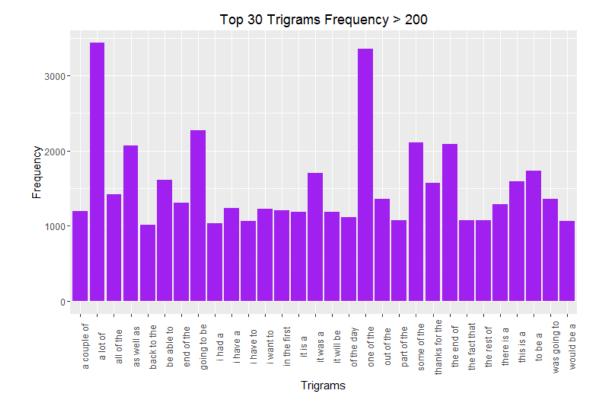
Bigrams

```
BigramTokenizer <- function(x) NGramTokenizer(x, Weka_control(min = 2,</pre>
max = 2))
text.Sample.Bigram <- TermDocumentMatrix(text.Sample, control =</pre>
list(tokenize = BigramTokenizer))
FreqTerms <- findFreqTerms(text.Sample.Bigram, lowfreq = 600)</pre>
text.Sample.Frequency.Vector.Bi <-
sort(rowSums(as.matrix(text.Sample.Bigram[FreqTerms,])),decreasing=TRUE
)
text.Sample.Frequency.Dataframe.Bi <- data.frame(word =</pre>
names(text.Sample.Frequency.Vector.Bi),freq=text.Sample.Frequency.Vecto
r.Bi)
ggplot(data=text.Sample.Frequency.Dataframe.Bi[1:30,],aes(x=word,y=freq
)) +
  geom_bar(stat="identity", fill="red") +
theme(axis.text.x=element_text(angle=90)) +
  labs(title="Top 30 Bigrams Frequency >600") +
  labs(x="Bigrams") + labs(y="Frequency")
```



Trigrams

```
TrigramTokenizer <- function(x) NGramTokenizer(x, Weka_control(min = 3,</pre>
max = 3)
text.Sample.Trigram <- TermDocumentMatrix(text.Sample, control =</pre>
list(tokenize = TrigramTokenizer))
FreqTerms <- findFreqTerms(text.Sample.Trigram, lowfreq = 200)</pre>
text.Sample.Frequency.Vector.Tri <-
sort(rowSums(as.matrix(text.Sample.Trigram[FreqTerms,])),decreasing=TRU
E)
text.Sample.Frequency.Dataframe.Tri <- data.frame(word =
names(text.Sample.Frequency.Vector.Tri),freq=text.Sample.Frequency.Vect
or.Tri)
ggplot(data=text.Sample.Frequency.Dataframe.Tri[1:30,],aes(x=word,y=fre
q)) +
  geom_bar(stat="identity", fill="purple") +
theme(axis.text.x=element text(angle=90)) +
  labs(title="Top 30 Trigrams Frequency > 200") +
  labs(x="Trigrams") + labs(y="Frequency")
```



Wordcloud

In this section, the analysis will be drawn on which string of words that people are going to say in different media outlets for this model. It is going to be divided in different n-gram model categories.

```
wordcloud(words=text.Sample.Frequency.Dataframe.Uni$word,max.words =
300, freq= text.Sample.Frequency.Dataframe.Uni$freq, scale = c(1,1),
random.order = F, colors =brewer.pal(20, "Dark2"))
```

wordcloud(words=text.Sample.Frequency.Dataframe.Bi\$word,max.words =
100, freq= text.Sample.Frequency.Dataframe.Bi\$freq, scale = c(2,1),
random.order = F, colors =brewer.pal(10, "Dark2"))

```
part of $\begin{align*}{0}$ the new some of $\tilde{w}$ over the and then would be a new able to he was out of a little like a little like a has been have to by the a few but the a great to do but i one of with the is the that is in my to get in a of to the can be on a i was as thei had is a of there is going to of a little like a was a of the can be on a i was as thei had is a of the can be on a i was as thei had is a of the can be on a i was as their had is a of the can be on a i was as their had is a little like a with the is the that is in my to get in a of the can be on a i was as their had is a of the can be on a i was a solution of a little like a little like a little like a has been have i and the for all you had a little like a little like a was a of the can be on a i was a little like a has been have is and the is and i was a little like a little l
```

```
wordcloud(words=text.Sample.Frequency.Dataframe.Tri$word,max.words =
200, freq= text.Sample.Frequency.Dataframe.Tri$freq, scale = c(3,1),
random.order = F, colors =brewer.pal(10, "Dark2"))
```

was one of looking forward to most of the if you want to get a to have a 2 you have to the fact that that I was according to the mas well as it will be Ē end of the **the** i want to was a be able to s not a or this is ai have a i had to one of my was going to the rest of think i when I was part of the back to the but it was to make a to get the there is no in new york a little bit i wanted to i need to

Next Steps for the Project

- With this analysis done, the next step is to create a shiny app to make the next word prediction based on the information that is provided in the report.
- The dataframes would be used to calculate its probability on the words that are used next.